Multiple Instance Regression with Structured Data

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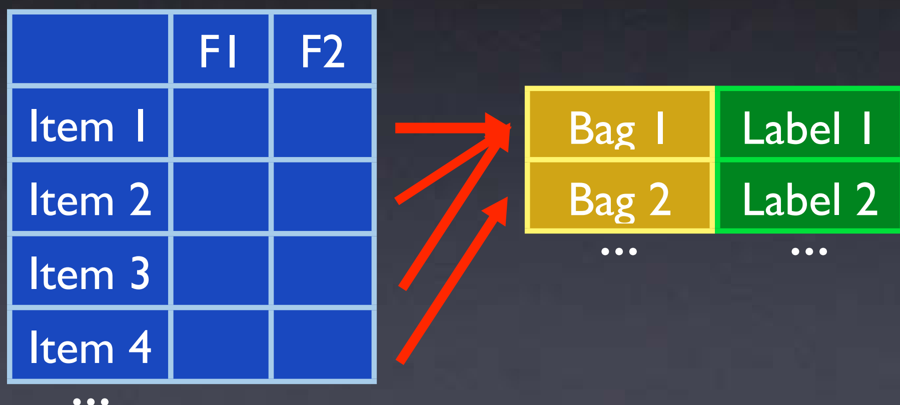
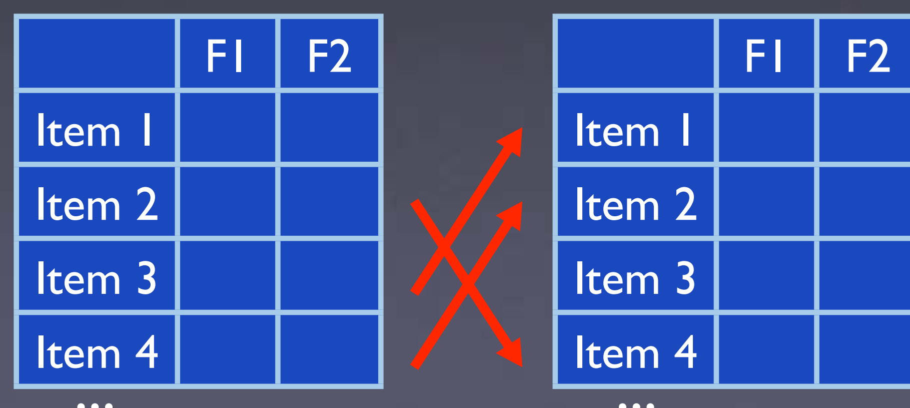
Data Structure Spectrum

Tabular Data

Multiple-Instance Data

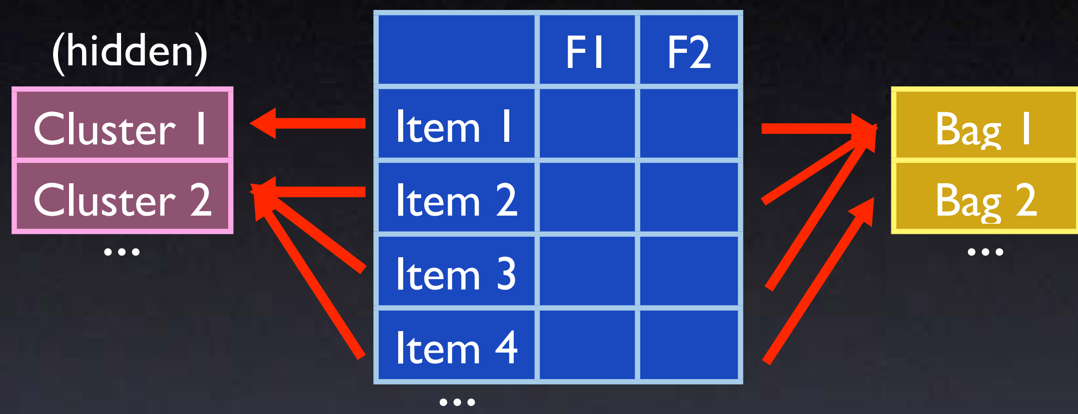


Relational Data



MIL with Structured Bags

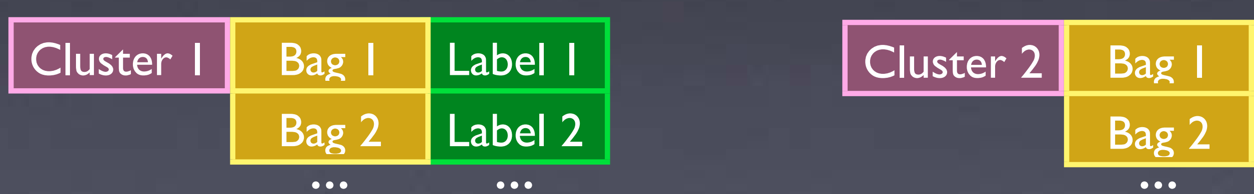
Bags contain sub-populations (clusters)



Only one cluster is relevant to the target concept

Relevant

Irrelevant



Items contribute to bag labels only through cluster membership

Structure =

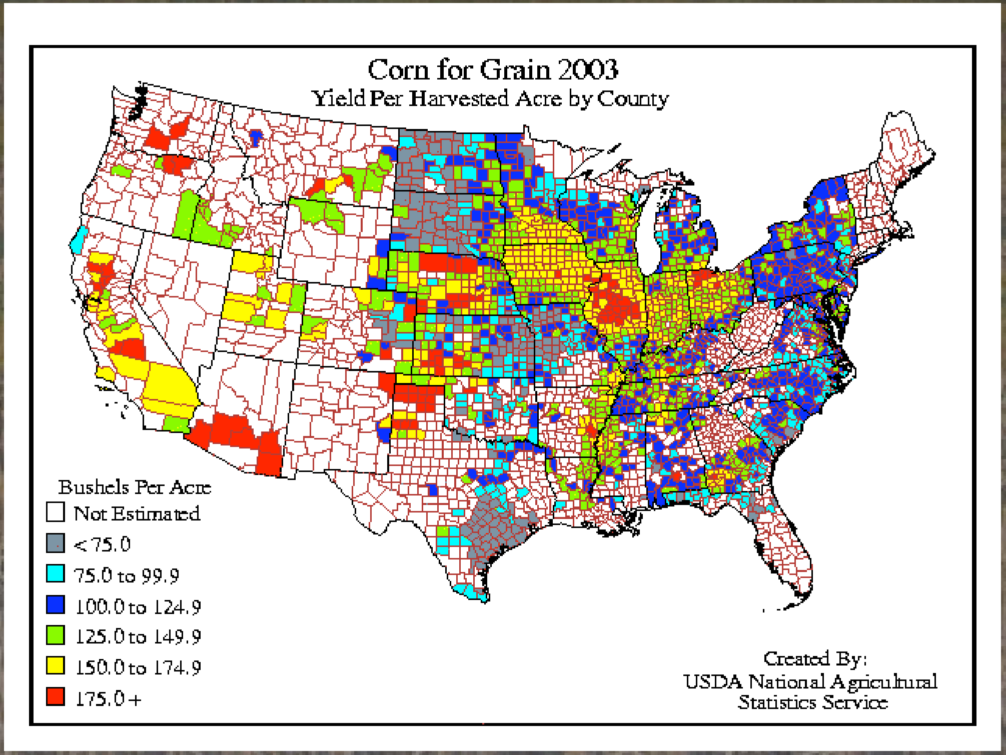
bag contents drawn from multiple distributions

What problems have this structure?

Predicting Crop Yield

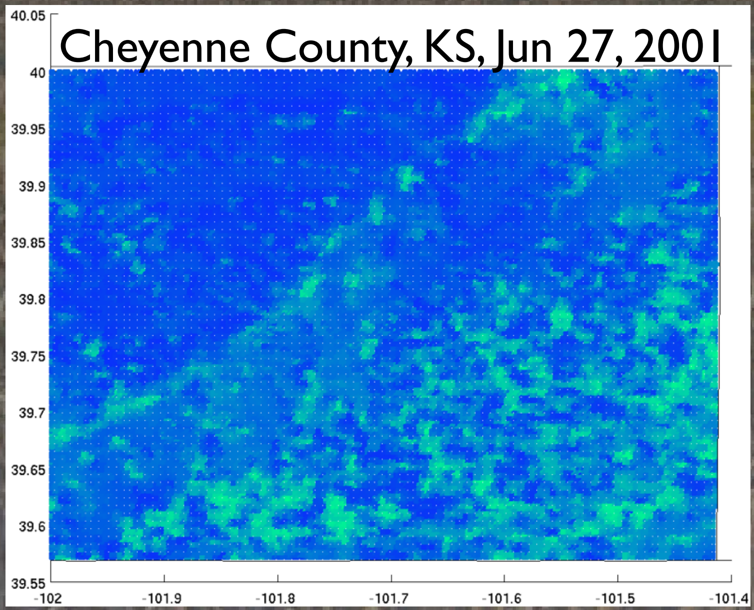
- USDA:
  - Post-harvest yield results per county, per crop
  - Could we predict yield earlier in the year?
  - Data = remote sensing: weekly observations, entire U.S.

- Benefits:
  - Inform agricultural markets
  - Enable more focused precision agriculture



Multiple Instance Problem

- Each county (bag of pixels):
  - 250 m/pixel = 30,000 - 300,000 pixels
  - One label per crop: bushels/acre
- Which ones are relevant?
  - Bags have structure
  - Sub-pixel mixing: Need to model degree of membership

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37 bu/acre of wheat
124 bu/acre of corn
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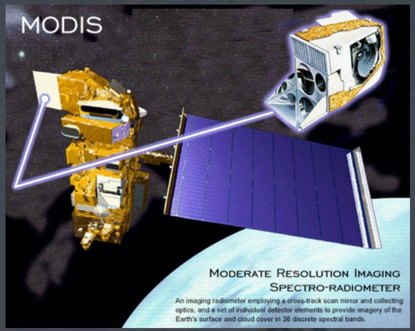
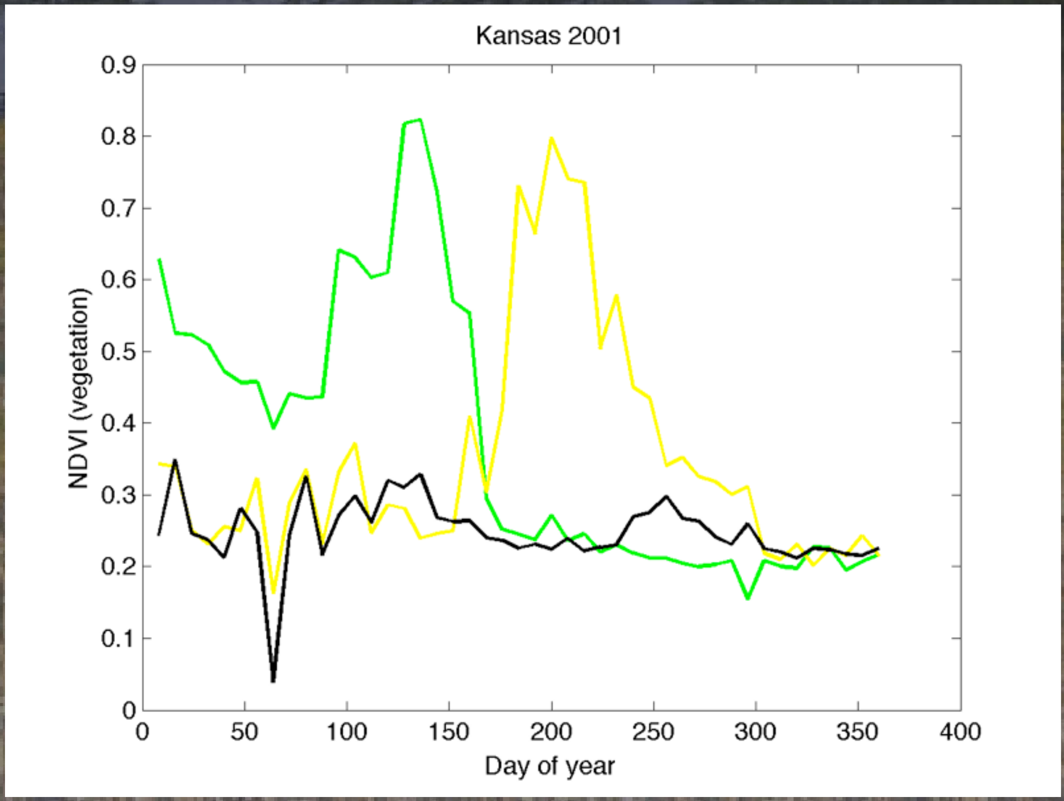
Instance = Time Series



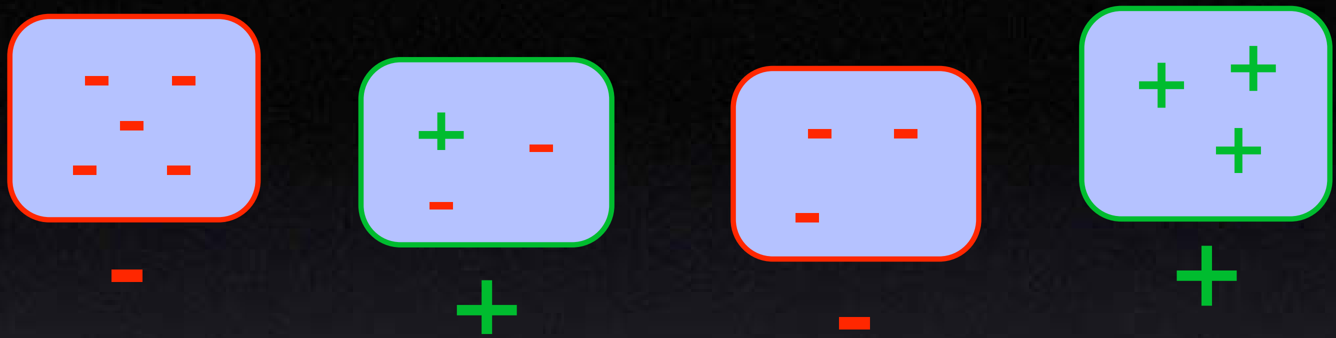
- MODIS: Red and NIR every 8 days

$$\text{NDVI} = \frac{\text{NIR} - \text{RED}}{\text{NIR} + \text{RED}}$$

- How early can we make good predictions?
- Time series can reveal crop type
  - Or at least crop vs. forest/city/etc.
  - Thus hinting at relevance to label



Multiple-Instance Learning



- Classification: >= 1 positive item -> positive bag [Dietterich et al., 97]
- MIL via Embedded Instance Selection (MILES) [Chen et al., 06]
  - Embed bags in item-similarity feature space,
    use feature selection to find relevant ones, use regular SVM
  - Application: region-based image categorization

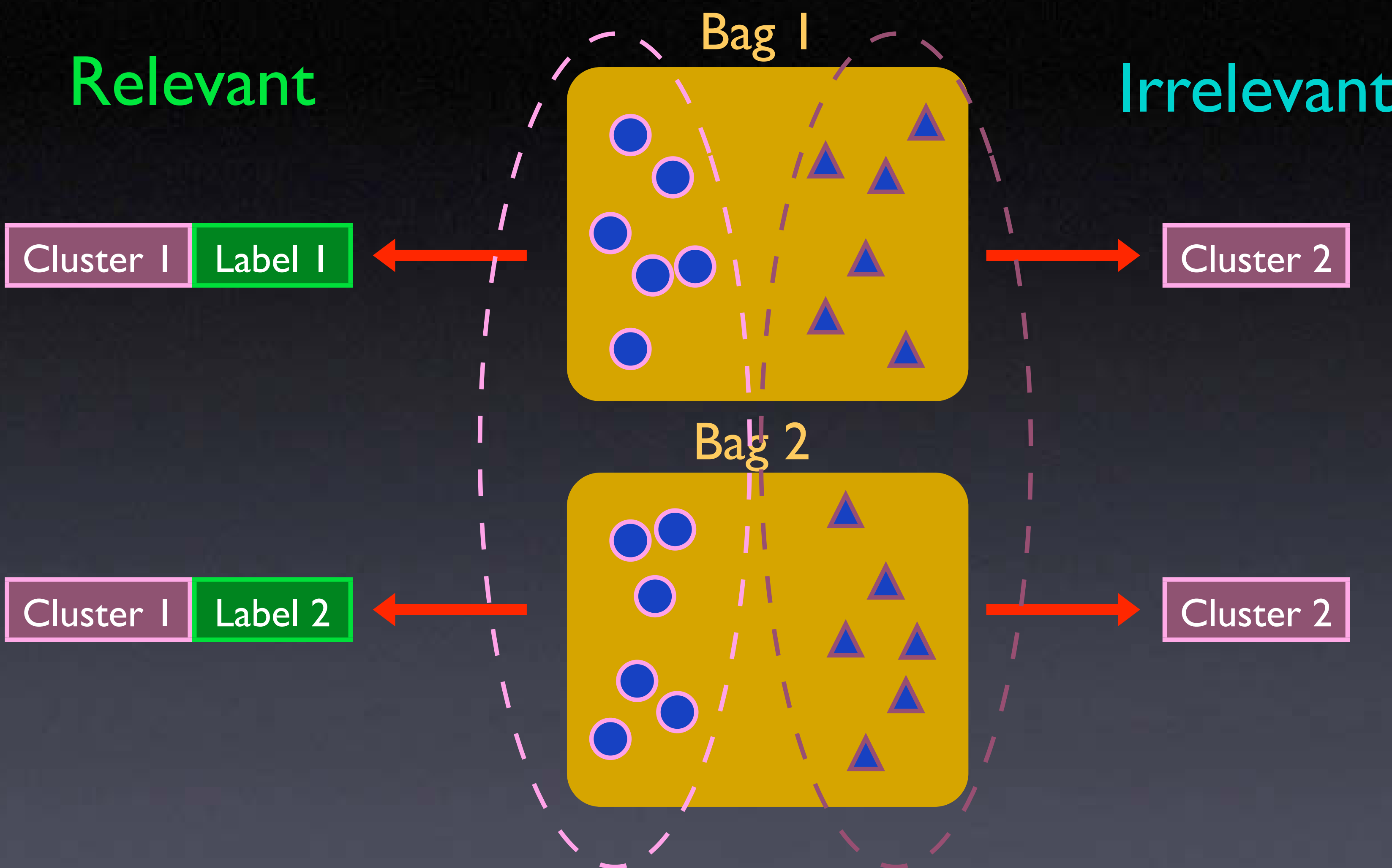
Multiple-Instance Regression

- Primary Instance Regression (PIR) [Ray & Page, 01]
  - Find single item that dictates bag label
  - Other items are noisy observations of primary

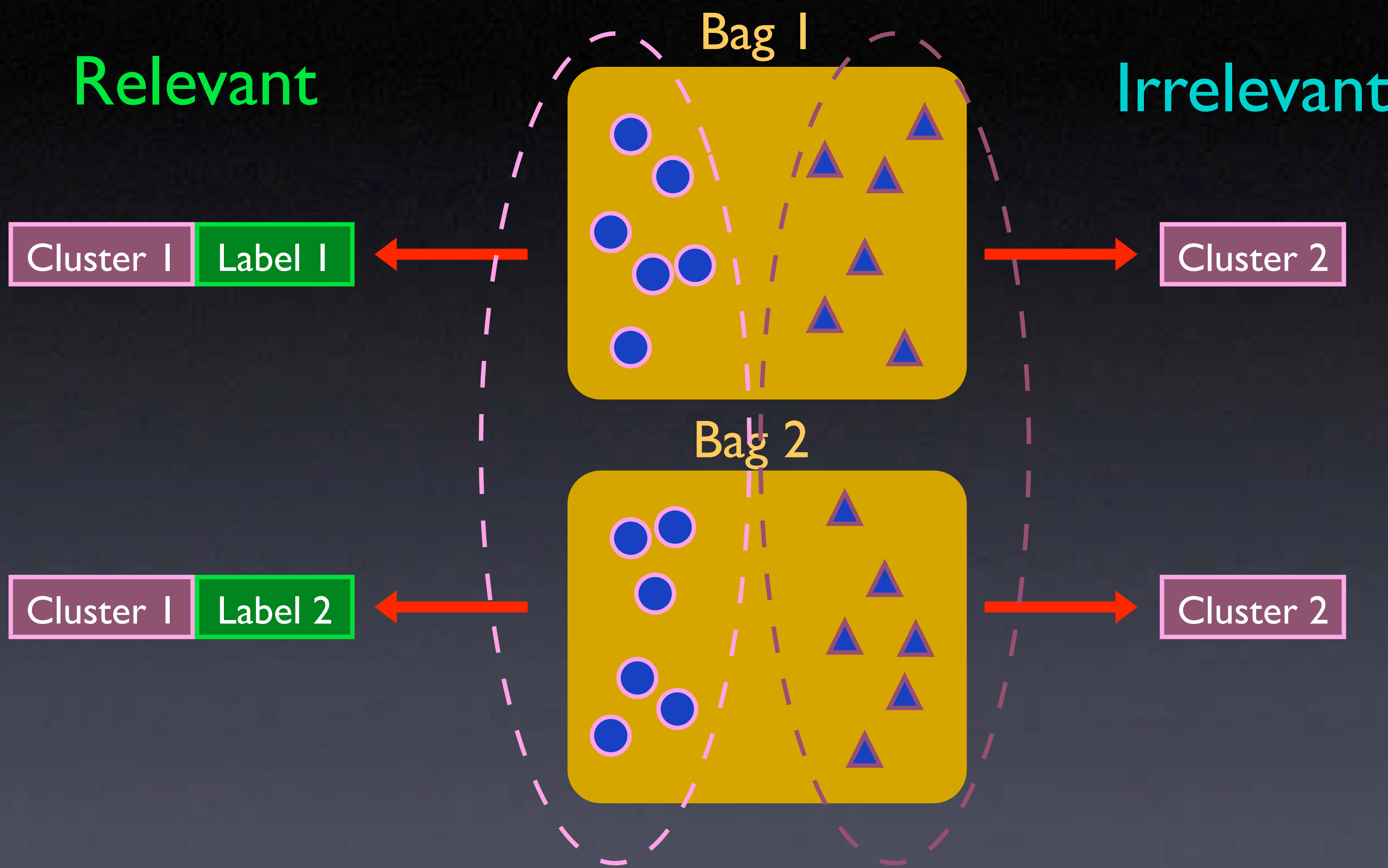
Our Solution: Cluster Regression Models

- Explicitly model bag structure, multiple populations
- Assumption: bag label derives from a subset of *similar* items (in input feature space)
  - Individual relevance per item
- Approach:
  1. Identify clusters of items
  2. Build one regression model per cluster
  3. Select model that best fits the bag labels

MIL with Structured Bags

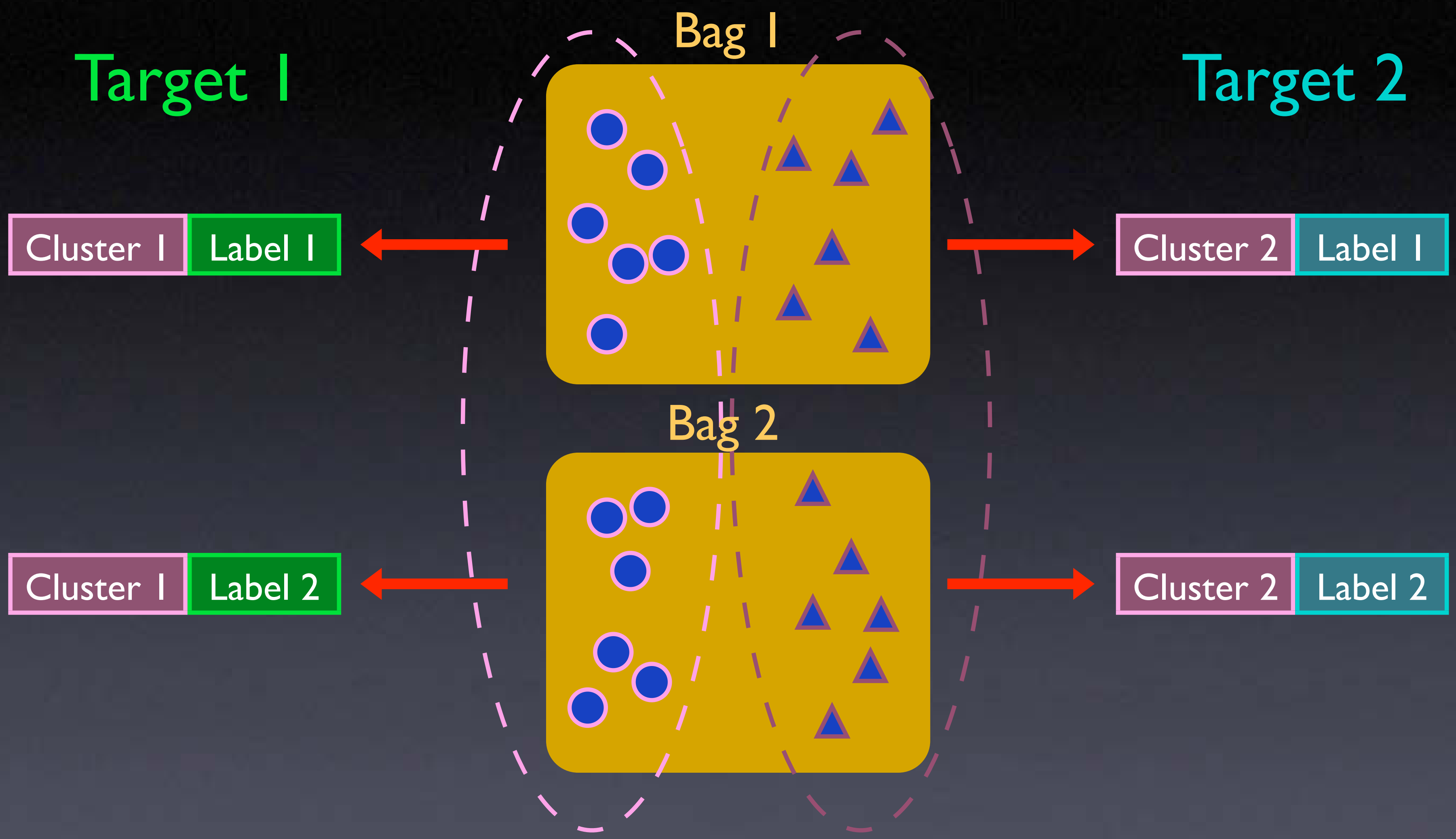


MIL with Structured Bags



Goal: infer cluster memberships to enable label prediction

MIL with Structured Bags



Goal: infer cluster memberships to enable label prediction

MI-ClusterRegress

1. Cluster entire collection of data into k clusters

Mixture model $$f(x_i) = \sum_{c=1}^{k} \alpha_c f_c(x_i) \qquad f_c(x) = \mathcal{N}(M_c, \Sigma_c)$$ Gaussian

2. Create weighted exemplar for bag B, cluster c

Membership prob. $$p(c|x_i) = \frac{\alpha_c p_c(x_i|M_c, \Sigma_c)}{p(x_i)} \qquad w_{cB} = \frac{1}{|B|} \sum_{i=1}^{|B|} p(c|x_i) x_i$$ Exemplar

3. Build k regression models
   - Model L_c: map all bag exemplars w_{cB} to bag labels
4. Select the regression model $L_{c'}$ that best fits the labels

MI-ClusterPredict

- Predicting the label of a new bag B':

1. Classify items in B' into the k clusters

Membership prob.
$$p(c|x_i) = \frac{\alpha_c p_c(x_i|M_c, \Sigma_c)}{p(x_i)}$$

2. Create an exemplar for the items in cluster c'

Exemplar
$$w_{c'B'} = \frac{1}{|B'|} \sum_{i=1}^{|B'|} p(c'|x_i) x_i$$

3. Use $L_{c'}(w_{c'B'})$ to predict the bag's label

Crop Yield: Methods Evaluated

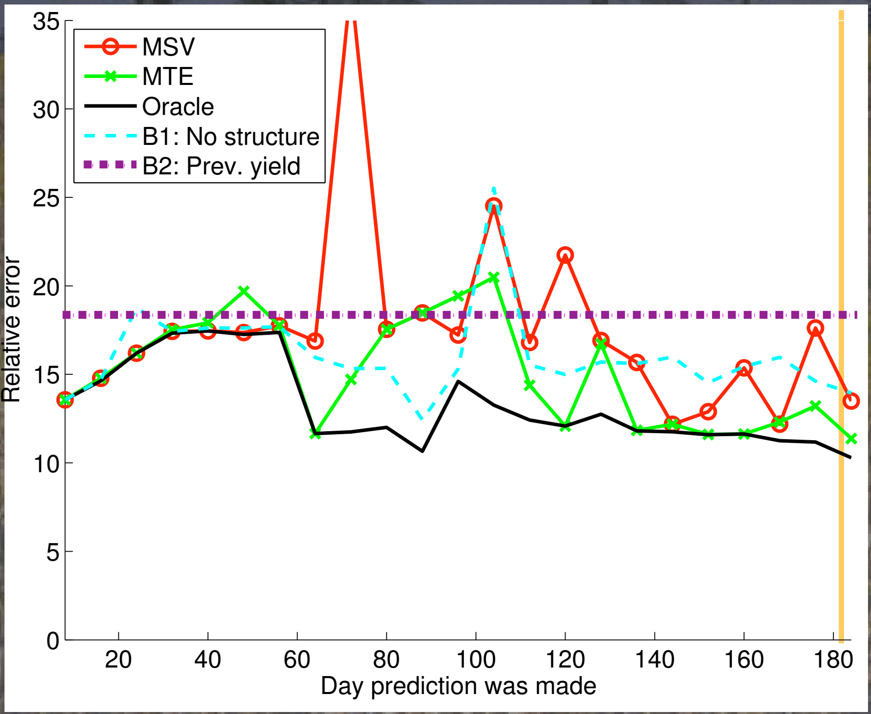
- MI-ClusterRegress Model Selection methods:
  - Complexity: minimum # of support vectors
  - Training: minimum error on training data
  - Oracle: minimum error on test data

- Baselines
  - B1: Exemplar = mean pixel (no structure)
  - B2: Last year's yield

Results: Train on '01-04, test '05

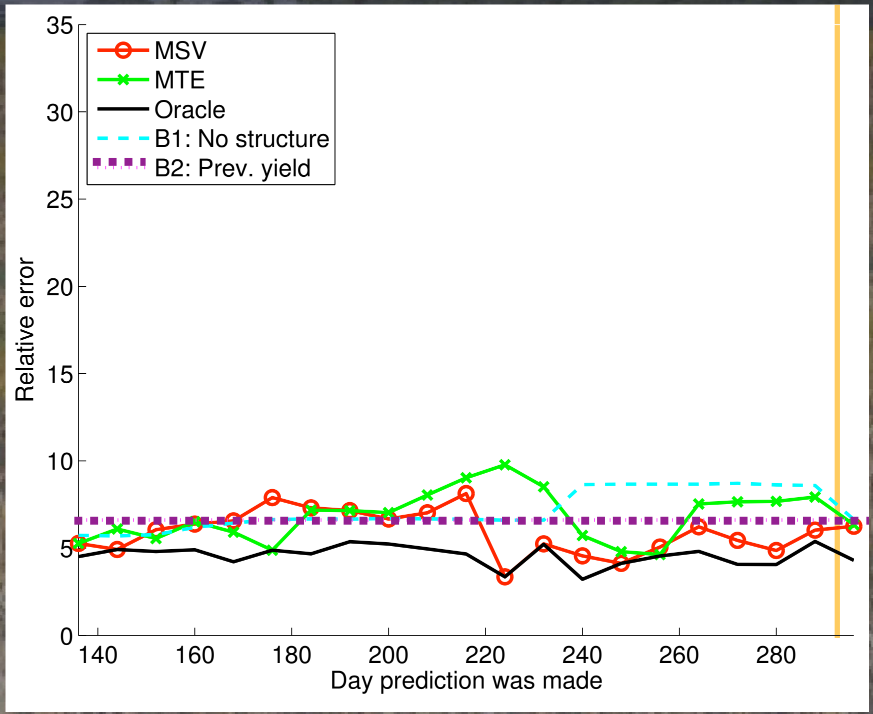
- CA: 42 counties, subsample 100 pixels/county
- Using K = 30 local models, select the best
- Same input data used to predict different crops

Harvest time



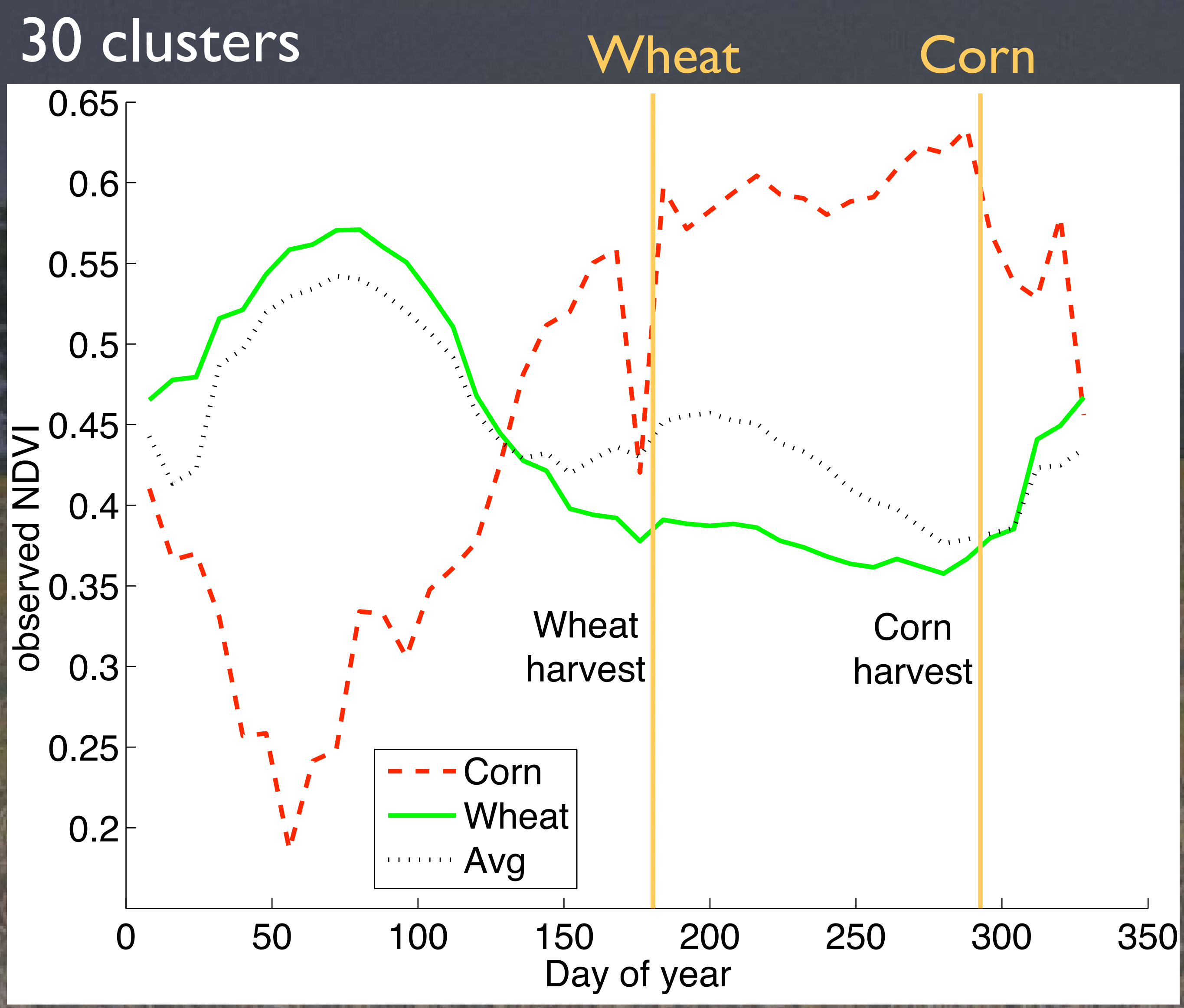
Wheat

Harvest time



Corn

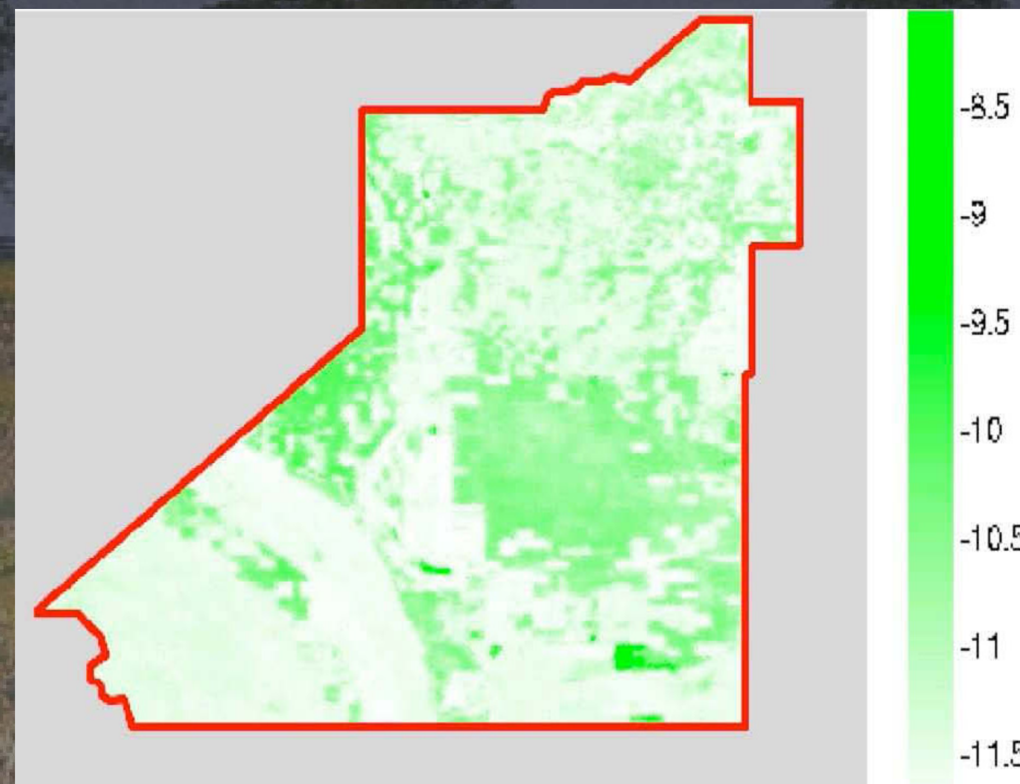
Model Selection: Clusters Chosen



Pixel Salience: Kings County, CA

Google Maps

Wheat Salience, Day 72



Conclusions and Future Work

- MIR with structured data: challenging new problem
- MI-ClusterRegress: Build per-cluster regression models that predict bag labels based on item relevance
- Crop yield prediction
    - 5-10% relative error in predictions 4 months before harvest
    - Bonus: item relevance provides per-crop maps
- Future work
    - Larger per-county samples, more crops, more counties
    - Other model selection heuristics
    - Relax Gaussian assumption on internal bag structure

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